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Electricity Demand Forecasting in Decentralised Demand Side Response for Blocks of Buildings

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Abstract

A downturn of centralised conventional fossil fuel fired power plants and increased proportion of distributed power generation adds to the already troublesome outlook for operators of low-inertia energy systems. The role of an emerging decentralised energy sector allows separation of local energy needs from major power networks. However, the diversion of energy generation means diminishing levels of system inertia on the network needs to be better monitored and controlled. Reducing the overall energy consumption at times of peak demand through demand-side response (DSR) is conducive to intelligent use of electrical power. However, in the absence of reliable demand forecasting measures, effective decentralised demand-side energy planning is often problematic. In this work we formulate a simple yet highly effective approach for forecasting univariate quantitative time series by utilising electricity demand in a decentralised demand-side optimisation model. The forecasting session is constructed initially through analysis of a chronological sequence of discrete observations. Interpretations concerning the generalisation of demand data shows behaviour that allows symbolic representation of the time series. Calculation of short-term forecasting problems have been obtained. Results for medium-term forecasts that extend beyond 12-months are also very promising. In addition to motivating the construction of a forecasting method, the main intention of this article is to derive a practical solution that will evolve a novel proactive approach to existing demand response mechanisms.

Keywords: Demand Response, Decentralised, Time Series Forecasting.

1 Introduction

An energy transition is needed to address environmental challenges of greenhouse gas-induced warming and increased carbon emissions, which are largely driven by a rapid growth in global population [1]. Constructing energy systems into more sustainable forms means electricity demand forecasting is necessary. As a broad guideline, research has shown that energy consumption in buildings accounts for approximately 40% of the world's energy resources and emits circa one-third of greenhouse gases [2,3]. Considering the long lifespans and complex challenges associated with regeneration of old building stock [4], more accessible energy retrofit initiatives to achieve energy saving targets are needed. Tangible measures that improve energy efficiency include lifestyle changes, e.g. use of smart meters [5], and distribution system planning as well as improving load and resource forecasting methods and approaches [6].

Analysis of temporal data and development of prediction forecasting models are often presented as multivariate time series prediction problems [7–10]. However, multivariate time series considers simultaneous time-dependant variables where each variable depends not only on its past values but also has some dependency on other variables. Thus, multivariate prediction may prove difficult to extract enough meaningful information that is useful for predicting future states. In contrast, a univariate time series with a single time dependent variable, may offer an improved alternative when prediction time horizons are small [11].

In this paper, we propose a univariate time series electricity demand prediction forecasting methodology. This work has uniqueness by using techniques that are in part long established in data mining processes that aim to extract useable patterns in huge data sets [12]. Furthermore, the approach is developed on the premise that a forecasting session is dependent on a look up table derived solely from a univariate quantitative time series. Thus, making the opportunity to deploy the prediction algorithm on low software complexity platforms a viable option.

The rest of the paper is structured as follows. Section 2 provides a brief description of related work. Section 3 introduces the proposed methodology for demand prediction forecasting. Results and discussions are provided in Section 4. Finally, in Section 5, the conclusions are provided with recommendations for future work.

2 Related Work

A conceptual framework that places an energy optimisation system (EOS), designed to optimise energy consumption in blocks of buildings, makes use of decentralised grid frequency [13]. The conceptual framework promotes using a univariate quantitative time series to help in the restoration of frequency equilibrium during network stress events. As a prelude to using grid frequency, this paper details a demand prediction methodology developed to influence the EOS optimisation cost function. Using pattern sequence similarity to derive a series of demand prediction look up tables, setting a demand prediction model forecast horizon to 4-hours offers consumers an opportunity to participate in a decentralised proactive demand response mechanism. A generalised block diagram that shows the contribution of demand prediction is shown at Figure 1.

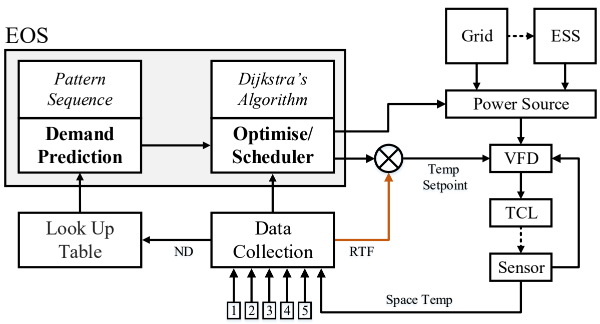


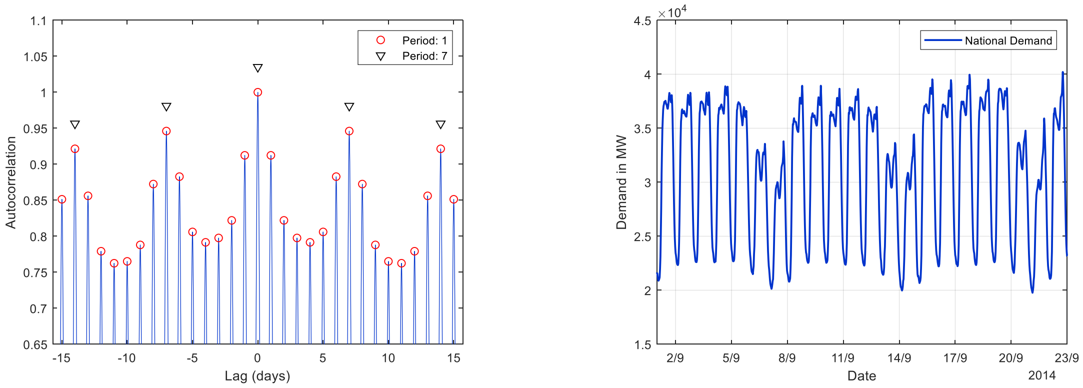
Figure 1 Information flow block diagram

3 Electricity Demand Time Series Forecasting Methodology

The proposed methodology is divided into two distinct parts. Analysis of a chronological sequence of discrete observations is first performed and the composition of the univariate one-dimensional time series is determined. In the second step, a dimensionality reduction technique is applied. The subsequent look up table allows the predictive forecast algorithm (PFA) to be deployed on inexpensive and low software complexity microcontrollers. The objective is to maintain an accurate 4-hour prediction horizon. However, results show this can be changed to much longer periods while maintaining competitive results.

3.1 Composition of Time Series

The Electricity System Operator (ESO) in Great Britain publishes historic national demand data [14]. The data represents the generation requirement and is the sum of metered generation recorded at 30-minute intervals. In this paper analysis is based on national demand data from 2005 to 2019; comprising 246,288 data items. The first task is to extract meaningful characteristics. Computing the autocorrelation of the time series identifies the periodicity of the signal. Figure 2 shows the time period between each peak is consistent with a typical weekly pattern consisting 5 similar weekday oscillations followed by 2 weekend day oscillations, also of similar form.



(a) (b)

Figure 2 (a) Autocorrelation shows weekly pattern, (b) UK National Demand profile

Regression is used to remove fluctuations in the time series and to identify potential seasonal and cyclic behaviour, that is regularly repeating patterns of highs and lows related to calendar time such as seasons, quarters, months and so on. The approach used to removing the trend from the time series first calculates the least squares regression line, then subtracts the deviations from the least squares fit line from the time series. Given the equation for a straight line is $y = bx + a$ where b is the slope of the line and a is the y-intercept, the best fit line for points $(x_1, y_1), \cdots, (x_n, y_n)$ is given by $y - \bar{y} = b(x - \bar{x})$ where

$$b = \sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) \,/ \sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{1}$$

and $a = \bar{y} - b\bar{x}$. In the absence of outliers, Eq. (2) is used to apply the min-max feature scaling which normalises the time series. Where the lower input range $l = 0$ and maximum of input range $u = 100$.

$$x' = l + [(x - x\mathrm{min})(u - l)]/(x\mathrm{max} - x\mathrm{min}) \tag{2}$$

A set made up of 14 distinct weeks, where each week identified commences on the Monday immediately following the lowest recorded demand data in each year (2005 to 2019), is identified. A 3-dimensional array (9×48×14) that characterises the set, where each page represents 1 week, is subsequently created. Measurements recorded at 30-minute intervals for each day are assigned to columns 1 to 48; the mean value of rows 1-5 (weekdays) and rows 6 and 7 (weekend days) are assigned to rows 8 and 9 respectively. A mean value of rows 8 and 9 are then computed to enumerate a generalised demand profile shape for any weekday and weekend day respectively.

A simple moving average of order n process given at Eq. (3) smooths the original demand data; where n represents a set number of observations for one month and year respectively.

$$y_t = \frac{1}{n}\sum_{i=t-n+1}^{t} y_i \tag{3}$$

Analysis reveals in addition to daily/weekly characteristics, the time series also displays seasonality and negative secular trend with constant variability. The general idea is to define a model from historical time series that enumerates the daily/weekly, seasonality and negative secular trend that can be used as part of the forecasting prediction algorithm. For seasonality, the basic route is to calculate the mean of each moving average 12-month period before applying a dimensionality reduction technique. Furthermore, in this strategy the negative secular trend is expressed in mathematical terms by using Eq. (1). Here, the coefficients for a polynomial that is a best fit (least squares method) of the given set of data are calculated.

The composition of the time series observed is characterised by 3 predominant features: (1) Day (weekday and weekend day), (2) Month and (3) Year. In the following subsections we first present a method to reduce time series feature dimensionality and then formulate the forecast prediction algorithm.

3.2 Dimensionality Reduction

Piecewise aggregate approximation (PAA), proposed by Keogh et al. [15], is a technique that reduces the dimensionality of a time series and for data representation. We choose to approximate the data with a piecewise coefficient such that the period between each change point is 2-hours. In this method, the normalised demand time series window of size n is first divided into k segments of equal length, and the average value of the data of the segments is then used as the representative value of each segment. Therefore, the demand time series PAA representation will be a k-dimensional vector $\bar{X}_i = \bar{x}_1, \dots, \bar{x}_n$ of the mean values of each segment. The dimensionality reduction calculation is computed by Eq. (4).

$$\bar{x}_i = \frac{k}{n}\sum_{j=\frac{n}{k}(i-1)+1}^{\frac{n}{k}i} x_j \tag{4}$$

The equation provides the mean of the elements in the equi-sized frames which makes up the vector of the reduced dimensional time series. The method is applied to the *day* and *month* features. A numerical investigation comparing different piecewise coefficients confirms reduced dimensionality while preserving enough information about the original data.

3.3 Symbolisation of each PAA Segment

Having transformed the time series into segments using PAA technique, the data is discretized; grouping the continuous input into a finite number of discrete bins. The translation means the data dimensionality can be reduced further and converted into a symbol string using symbolic aggregate approximation (SAX), i.e. each region is assigned a symbol according to the determined change points. In the context of data mining, SAX is comparable to other techniques including discrete Fourier transform and discrete wavelet transform, while requiring less storage [16]. This strategy ensures the forecasting algorithm is more transferrable to low software complexity microcontrollers. In this work the SAX symbol string is a 4-bit binary representation of the discrete bin the continuous input was assigned after discretization.

3.4 Predictive Algorithm Look Up Table

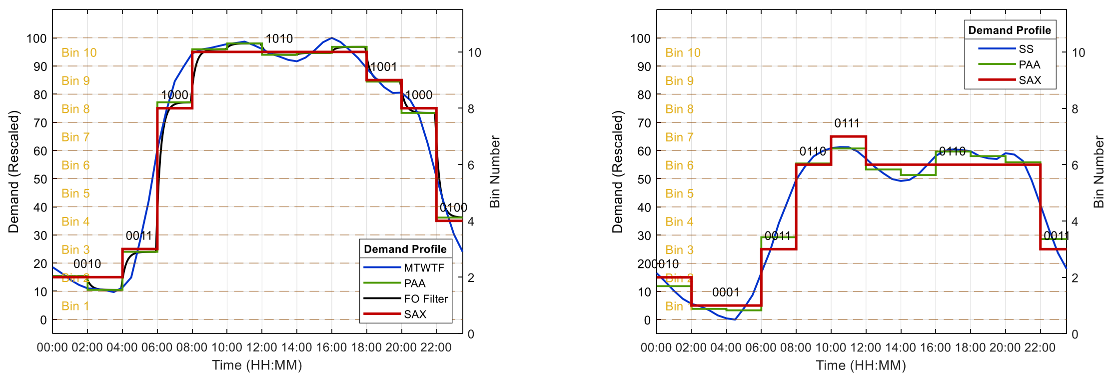
As an alternative to making use of techniques based on pattern sequence similarity, the proposed methodology instead extracts singularities of bin data to create a series of look up tables (LUT). Given the length of each piecewise segment, the process of creating look up tables for weekday, weekend day and month PAX or SAX representations is straightforward. In this paper we present a LUT based on piecewise coefficient only. Assuming each PAA segment is 2-hours, a key observation is that the time series original 246,288 data items is reduced to 12 elements for each *day* and *month* feature (Table 1). To perform forecasting up to 1 calendar month requires weekday and weekend day LUT. Extending the time horizon further up to 12-months requires the month LUT, and beyond 12-months, a seasonal adjustment is required. The mathematical representation of seasonal adjustment is derived using a straight-line approximation of the 12-month moving average, i.e. $y = bx + a$ where $b = 0.000442$ and the y-intercept a, is set to the initial calculated weekday value.

Table 1 Piecewise Coefficient Look Up Table

Weekday	Weekend Day	Month
[15.34, 10.47, 24.00, 77.11, 95.94, 98.02, 93.98, 94.64, 96.79, 84.46, 73.32, 36.16]	[11.87, 3.80, 3.29, 29.24, 55.42, 60.76, 53.30, 51.31, 59.67, 58.02, 55.84, 28.58]	[40.11, 32.81, 30.23, 29.39, 29.00 34.97, 44.18, 57.63, 61.01, 65.00, 63.33, 53.23]

4 Results and Discussion

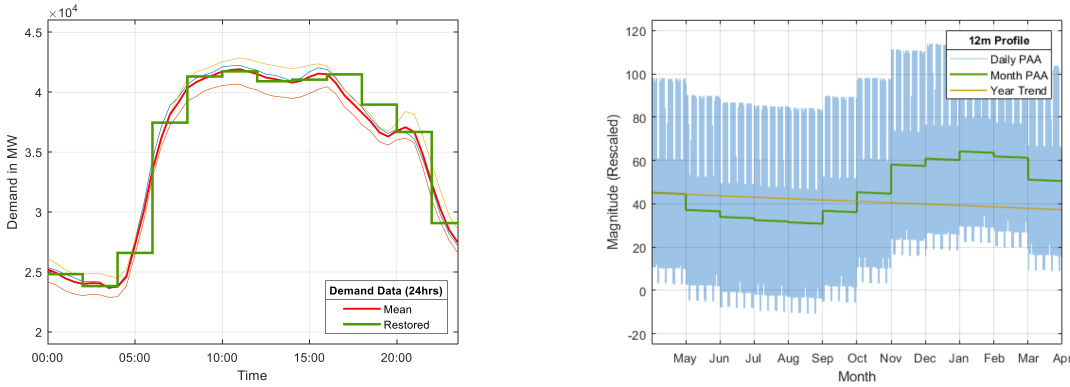
The above methodology has been applied to the UK electricity demand data (2005 to 2019). Figure 3 shows demand data after dimensionality reduction using PAA has been applied and where each region has been subsequently assigned a 4-bit binary representation of the discrete bin the continuous input was assigned after discretization. A visual representation of generalised weekday and weekend days are shown. The effect of SAX encoding reduces the weekday and weekend day LUT further from 12 elements to 7. Although discretization and SAX encoding offers the potential to reduce PAA dimensionality further, in the context of an EOS where a balance between accuracy and how easily the algorithm can be deployed to low software complexity microcontrollers, a prediction forecast based on PAA and discretization has the potential to offer greater benefit. In this instance encoding PAA bin categories to binary string format should be a straightforward task. Furthermore, applying a first-order edge-preserving filter to PAA data (Figure 3 (a)) provides a competitive smoother during transition from one frame to another.



(a) (b)

Figure 3 24-hour period PAA (2-hour) & SAX representations (a) weekday, (b) weekend day

Experimental results of reconstructing prediction forecasts by limiting the input to piecewise coefficient only, over a 24-hour period (weekday) where the PAA segment is set to 2-hours, is shown in Figure 4 (a). The plot compares the reconstructed PAA representation with mean values of selected weekday demand profiles extracted from the 3-dimensional array introduced earlier. Figure 4 (b) shows a 12-month predicted demand data profile calculated using weekday PAA LUT; *month* and *year* trend features are also shown.



(a) (b)

Figure 4 Restored Demand Data (a) 24-hour PAA (2 hour) format, (b) 12-month period

5 Conclusion

The main contribution of this paper is to show that a series of simple data transformations provide an effective representation of demand time series. More sophisticated models are available, however in the context of a decentralised Energy Optimisation System (EOS) we have demonstrated the features offer distinct advantages when considering deployment to low software complexity platforms. This finding suggests that the behaviour of exiting energy optimisation technologies may benefit from similar approaches. For example support for energy planning of isolated islands or domestic households. In future work we intend to explore the feasibility of substituting LUT where assigned values originate from historical data, with real-time grid frequency data measured locally (decentralised).

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